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A predictive model of burn severity based on 20-year satellite-inferred burn severity data in a large southwestern US wilderness area

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ABSTRACT

We describe and then model satellite-inferred severe (stand-replacing) fire occurrence relative to topography (elevation, aspect, slope, solar radiation, Heat Load Index, wetness and measures of topographic ruggedness) using data from 114 fires > 40 ha in area that occurred between 1984 and 2004 in the Gila Wilderness and surrounding Gila National Forest. Severe fire occurred more frequently at higher elevations and on north-facing, steep slopes and at locally wet, cool sites, which suggests that moisture limitations on productivity in the southwestern US interact with topography to influence vegetation density and fuel production that in turn influence burn severity. We use the Random Forest algorithm and a stratified random sample of burn severity pixels with corresponding pixels from 15 topographic layers as predictor variables to build an empirical model predicting the probability of occurrence for severe burns across the entire 1.4 million ha study area. Our model correctly classified severity with a classification accuracy of 79.5% when burn severity pixels were classified as severe vs. not severe (two classes). Because our model was derived from data sampled across many fires over a 20-year period, it represents average probability of severe fire occurrence and is unlikely to predict burn severity for individual fire events. However, we believe it has potential as a tool for planning fuel treatment projects, in management of actively burning fires, and for better understanding of landscape-scale burn severity patterns.

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1. Introduction

As a keystone disturbance process, fire influences local, regional and global processes (Agee, 1993). In recent decades, fires have burned millions of hectares in the western US costing billions of dollars to contain and suppress (www.nifc.gov), likely reflecting both a legacy of fire exclusion and climate (Westerling et al., 2006). Many people are concerned that future fires will be larger and more severe (Running, 2006, NIFC, 2009) as Miller et al. (2009) demonstrated for recent fires in the Sierra and Cascade mountains of California. Large, stand-replacing fires are difficult to suppress, and can have significant ecological consequences when resulting in debris flows (Cannon and Reneau, 2000), accelerated soil erosion (Pannkuk and Robichaud, 2003) and changes in dominant vegetation type post-fire (Savage and Mast, 2005).

Burn severity indicates the magnitude of ecological change associated with a wildfire (see review by Lentile et al., 2006a). Here, we infer burn severity from Landsat satellite imagery pre- and post-fire, which largely reflects changes in overstory vegetation post-fire relative to pre-fire conditions (Lentile et al., 2006a).

Spatial patterns of burn severity over time are poorly understood. Topography, vegetation and climate interact in complex ways to influence fire extent and fire occurrence across a range of spatial scales (Stephens, 2001; Rollins et al., 2002). Paleoecological data suggest that fire extent and vegetation types have varied with past climate variability (Whitlock et al., 2003), and recent research has linked Holocene warming to severe, stand-replacing fires in dry pine forests in Idaho (Pierce et al., 2005). Land use is also important, as decades of fire exclusion have altered stand structure and surface fuels loads, likely contributing to fire regime changes in forests that once burned frequently (Covington and Moore, 1994; Moore et al., 2004).

Severe fire has been related to vegetation and topography for individual large fire events. Odion et al. (2004) described patterns of severe fire occurrence within a large fire in central Oregon. Lentile et al. (2006b) used hundreds of field measurements and remote sensing to evaluate the relative influence of stand structure and topography on severe fire occurrence within the 2000 Jasper Fire in the Black Hills of South Dakota. Alexander et al. (2006)

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examined the occurrence of severely burned areas within two fires in northern California and southern Oregon. Few studies have encompassed burn severity from many fires at once burning over decades (Holden et al., 2007; Miller et al., 2009), and so we lack a general understanding of the patterns of burn severity from many fires across gradients of vegetation and topography through time. Availability of pre- and post-fire Landsat images from the Monitoring Trends in Burn Severity (MTBS) project (http://fsgeodata.fs.fed.us/mtbs/) will greatly facilitate investigation of burn severity relative to topography, land use, climate, vegetation and disturbance history, something that is sorely needed (Morgan et al., 2001).

Land managers require tools that can help predict where and when severe, stand-replacing fires are likely to occur. When charged with managing the impacts of fire and fuels management on streams, fish, and other resources (Dunham et al., 2003; Rieman et al., 2003), predictive models of burn severity would help them in deciding where and when to suppress fires and manage fuels, and how aggressively. In this analysis, we chose to use inferences from pre- and post-burn satellite imagery of recent fires and topography. Burn severity inferred from differenced pre- and post-fire satellite imagery is available for many fires that have burned across a range of weather and climate conditions offering relatively consistent data on post-fire effects over large areas. Given the tremendous complexity of fire behavior and landscape–fire interactions, empirically based methods of predicting burn severity have the potential to capture complex relationships between vegetation, topography and fire behavior that may be difficult to model with physically based fire behavior models or gradient modeling approaches.

The research objectives of this analysis were two-fold. First, we evaluate 20 years of satellite-derived burn severity data with respect to topography and Potential Vegetation Type (PVT) across the Gila National Forest (Gila NF). Second, we develop a predictive model describing the probability of severe fire occurrence relative to a suite of topographic variables.

Most of the fires (90 of 114 fires and more than 80% of the area burned) we analyzed occurred within the Gila Aldo Leopold Wilderness Complex (GALWC), under relatively natural conditions. Within the wilderness, some fires are suppressed, but naturally ignited fires are often managed with limited suppression under the Wildland Fire Use program adopted there in 1974 or because they are low priority for suppression when other fires are threatening people and homes. Pioneering fire management efforts in the GALWC have made it a model for wilderness fire management in the United States (Burke, 2004). We take advantage of this rich history of large fires that burn during the natural fire season and with relatively little influence of roads, grazing, and logging to examine broad-scale patterns of severe fire occurrence and their association with vegetation and topography.

2. Methods

2.1. Study areas

Our research focused on the 1.4 million ha Gila National Forest in New Mexico, USA (Fig. 1). This area encompasses diverse landforms and topography. Many of the fires included in this study burned in the central and northern portion of the Gila Wilderness, where extensive stands of ponderosa pine and mesic ponderosa pine/Douglas-fir forests grow on broad, flat mesas. These forests transition into mixed-conifer and spruce-fir forests to the north, where the Mogollon Mountains rise to an elevation of 3200 m. Steep, rugged terrain dominates the Diablo and Pinos Altos ranges to the south. Precipitation in our study area is bimodal, occurring mainly in the winter, and following a typically dry period in the spring, as monsoon rain storms that begin, on average, in the first week of July (Sheppard et al., 2002). Lightning is frequent at mid and upper elevations in our study area (Rollins, 2001).

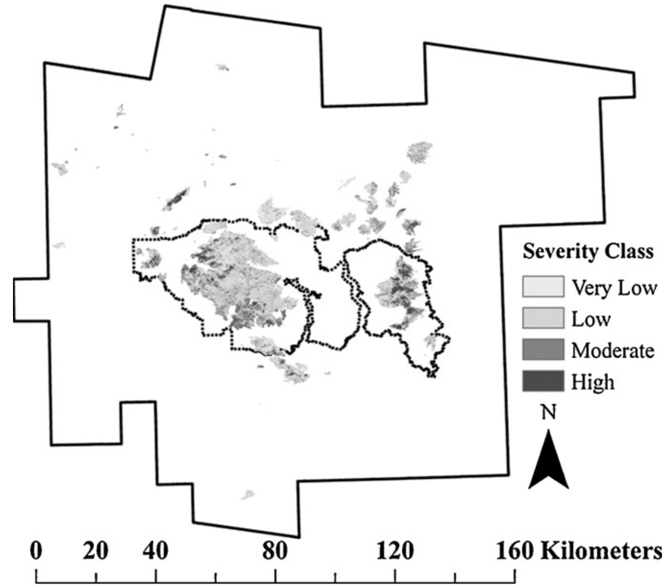

Fig. 1. Burn severity atlases (1984–2004) for the 1.4 million ha Gila National Forest in New Mexico. Fires varied in burn severity (shaded polygons, 114 fires burned 152,800 ha) as interpreted from Landsat satellite imagery using the Relative differenced Normalized Burn Ratio (RdNBR). Solid dark line is the Gila NF boundary. Dotted inner line denotes the Gila and Aldo Leopold Wilderness Complex boundary.

2.2. Burn severity atlas construction and analysis

A digital burn severity atlas including all fires >40 ha that occurred in 1984–2004 was created for the Gila National Forest using pre- and post-fire Landsat images provided by the Monitoring Trends in Burn Severity (MTBS) project (http://fsgeodata.fs.fed.us/mtbs/). All images were terrain corrected and converted to reflectance following protocols developed as part of the MTBS program. Pre- and post-fire spring scenes (15 May–15 July) in the Gila NF were processed using the Relative Differenced Normalized Burn Ratio (RdNBR) (Miller and Thode, 2007). The RdNBR is a variant of the dNBR, a spectral index first developed by Lopez Garcia and Caselles (1991) to map burned areas and then later used by Key and Benson (2005) to assess post-fire effects. Relative to dNBR, the RdNBR showed stronger and more linear correlations with field data from our study and is appropriate given the prevalence of open-canopy vegetation in our study area.

Each fire was manually digitized on-screen using a combination of dNBR and Landsat images. Digital fire perimeter databases, also called a fire atlas or a digital polygon fire history (produced by the GIS analyst on the Gila National Forest) were used to identify names and dates of major fires. Landsat bands 7:4:1 color composite and RdNBR images created for each fire were then used to verify the location of fires documented in the fire perimeter database and to locate additional smaller fires visible on the imagery but not in the fire perimeter databases. The resulting perimeters were then used to subset the RdNBR for each fire in ArcGIS (v. 9.2; ESRI, Inc. 2005). More than 40,000 ha burned multiple times during the period of our study (26% of the 153,000 total ha burned). Inclusion of recently reburned areas could confound our overall interpretation of burn severity patterns. Therefore, we excluded these data from this analysis by assigning these areas in the RdNBR a value of the first fire occurrence. Burn severity patterns within reburned areas are the subject of future research.

2.3. Field data collection

Burn severity on the ground was measured using Composite Burn Index (CBI) on 30 m diameter plots (Key and Benson, 2005) between 20 May 2004 and 20 July 2004. Within the perimeter of the 48,000 ha, 2003 Dry Lakes Fire, 109 sampling points were randomly located and stratified by four burn severity classes using a 23 October 2003 post-fire Landsat TM-derived Normalized Burn Ratio (NBR) image provided by the Remote Sensing Application Center. Field plots were randomly assigned to each severity class (unburned, low, moderate and high severity) using a GIS and then located in the field using GPS navigation.

Applying the CBI in the field post-fire requires an ocular assessment of the degree of change in multiple soil and vegetation strata as a result of the fire. While CBI is subjective, we were confident in the consistency of our estimates after spending three months collecting fuels, understory vegetation and forest structure data within the burned area the previous year. The CBI is a useful tool for rapidly assessing post-fire change and relating that change to reflected radiation detected by a satellite sensor. We removed two CBI measures from final CBI estimates (change in species composition, change in soil color) because they were difficult to objectively quantify in the field. We also removed estimates of medium and large-diameter fuel consumption and bole char height because we felt they were unlikely to be detectable by the Landsat sensor. These estimates were collected in the field but removed from the final CBI values that were used to validate the RdNBR. Comparison of scatter plots using both the full and modified CBI values showed that the removal of these variables had little overall effect on the final CBI measure (correlation between CBI and dNBR remained the same at 0.78).

Burn severity images for each fire were classified into four severity classes (unchanged, low, moderate, high), with break-points for each severity class defined based on CBI data. Because post-fire ecological effects occur along a continuum, classification of burn severity data may reduce their sensitivity. However, doing so simplifies data analysis and interpretation. We classified "severe" as burned areas where more than 75% of pre-fire overstory tree foliage volume was black or red post-fire, corresponding to a CBI value of 2.2 (RdNBR $\geq$ 665). Scatter plots of RdNBR and the CBI stratified by PVT showed no patterns of separation. Therefore, the same threshold was applied across all vegetation types. This slightly conservative threshold was selected based on the assumption that some delayed mortality was likely to occur in the years following the fire. Because we lack field data on burn severity for previous fires, CBI data from this one 2003 fire was used to set thresholds for all burns in the 20-year record. However, comparison of pre- and post-fire high resolution digital aerial photographs suggests that for three fires through time (1993, 1996, and 1997), fire-created canopy openings in ponderosa pine, Douglas-fir and mixed-conifer forests are mapped with a high degree of accuracy when this threshold is applied to earlier fires (data not shown).

2.4. Data analysis

We used sixteen independent variables in our analyses. Potential Vegetation Type (PVT) is a classification of biophysical setting named for the vegetation that would occur at a site after long periods without disturbance. We used a PVT classification developed by Keane et al. (2000) for the Gila National Forest as a stratifying variable. Fifteen independent variables were derived from a 30-m digital elevation model (http://ned.usgs.gov/) (Table 1). These included elevation (ELEV), an interaction between slope and aspect (SAT) (slope $\times$ COS[aspect]) (Stage, 1976), Heat Load Index (HLI) (McCune and Keon, 2002), solar radiation (SOLAR) (Fu and Rich, 1999) and a Compound Topographic Index (CTI) (Moore et al., 1993). Three measures of terrain ruggedness and variability (Dissection (DISS) (Pike and Wilson, 1971), Roughness (ROUGH) (Murphy et al., in press) and Elevation Relief Ratio (ERR) (Evans, 1972)) were also included and calculated using 3 $\times$ 3 and 15 $\times$ 15 and 27 $\times$ 27 window sizes. Finally, the hierarchical slope position (HSP) described by Murphy et al. (in press) was also included. All variables were classified using equal interval breaks for Bayesian conditional probabilities. Roughness, dissection and elevation relief ratio indices were excluded from Bayesian conditional probabilities because classified forms of this variable are difficult to interpret.

Table 1
Predictor variables included in Random Forest models.

Variable	Description	Reference
PVT	Potential Vegetation Type	Keane (2000)
ELEV	Elevation (meters)	USGS (1999)
SAT	Transformed slope/aspect	Stage (1976)
HLI	Heat Load Index	McCune and Keon (2002)
CTI	Compound Topographic Index	Moore et al. (1993)
SOLAR	Solar radiation (April–July)	Fu and Rich (1999)
DISS3	Modified dissection coefficient (3 $\times$ 3)	Pike and Wilson (1971)
DISS15	Modified dissection coefficient (15 $\times$ 15)	Pike and Wilson (1971)
DISS27	Modified dissection coefficient (27 $\times$ 27)	Pike and Wilson (1971)
ROUGH3	Topographic roughness (3 $\times$ 3)	Murphy et al. (in press)
ROUGH15	Topographic roughness (15 $\times$ 15)	Murphy et al. (in press)
ROUGH27	Topographic roughness (27 $\times$ 27)	Murphy et al. (in press)
ERR3	Elevation relief ratio (3 $\times$ 3)	Evans (1972)
ERR15	Elevation relief ratio (15 $\times$ 15)	Evans (1972)
ERR27	Elevation relief ratio (27 $\times$ 27)	Evans (1972)
HSP	Hierarchical slope position	Murphy et al. (in press)

We used two methods to analyze patterns of severe fire occurrence with respect to vegetation and topography. First, relationships between individual predictor variables and severe fire occurrence were graphed and assessed using conditional probabilities in the Bayes extension for Arcview 3.3 (ESRI 2002) (Aspinall, 1992, 2000). Conditional probabilities describe the likelihood of severe fire occurring with respect to each independent variable given the proportion of that variable within the total area burned. Conditional probabilities were calculated for eight classified topographic variables individually using a binary (severe vs. other burned) grid of total burned area as the response.

Second, we use a variant of Classification and Regression Trees called Random Forests (Breiman, 2002) to assess the ability of landscape variables to predict severe fire occurrence. We used the Random Forest package developed for R (R core Development Team 2007) by Liaw and Weiner (2002). Random Forest implements a bootstrapping procedure whereby approximately 66% of the data are used in a classification tree with the remaining data used as a validation data set (termed the "out of bag" sample). The Random Forest algorithm uses this bootstrapping procedure to generate thousands of classification trees. In addition to the bootstrap replicates, multiple variables are permutated through each node as a means of preventing over-fit and assessing the mean square error (MSE) variable importance. This method is computationally very intensive, but has yielded robust predictions across a variety of applications (Prasad et al., 2006; Rehfeldt et al.,

Table 2
Area burned by burn severity class (RdNBR) within each Potential Vegetation Type (PVT) on the Gila NF (1984–2004).

PVT	% of PVT in study area	Low (ha)	%	Moderate (ha)	%	High (ha)	%	Area burned (ha)
Sparse veg.	10	1,030	62	4,540	27	1,809	11	16,609
PJ-Oak	39	18,856	75	4,937	20	1,242	5	25,034
Ponderosa pine	19	33,412	74	9,467	21	2,085	5	44,965
Douglas-fir	7	24,223	67	8,417	23	3,757	10	36,397
Mixed-conifer	4	10,917	55	4,774	24	4,043	20	19,733
Spruce-Fir	1	1,625	49	705	21	962	29	3,292
Riparian	1	3,388	50	2,692	39	764	11	6,844
Area burned		102,680	67	35,532	23	14,661	10	152,874

Only fires >40 ha in size are included. Percentages are of the area burned within each PVT. Of the 1.4 million ha on the Gila National Forest, 11% (152,874 ha) burned at least once within the PVTs listed.

2006). We applied the Random Forest algorithm using RdNBR data classified into two classes (severely burned vs. other) and into three classes (low, moderate and high burn severity classes). We used fourteen topographic variable derived from a 30-m digital Elevation Model (Table 1). We ran Random Forest for all PVTs combined with PVT included as an independent variable in the model, and then ran separate models for each individual PVT. The low proportion of severe relative to other burn severity classes initially led to slight overprediction. To account for this bias, we used a dual-phase stratified random sampling routine to select more balanced proportions of each severity class across the range of PVT's. Model error stabilized after ~1000 bootstrap replicates, so final models were run with 2000 replicates. The *m* parameter (number of variables permuted through each node) was optimized with four variables selected at each node permutation.

3. Results

The RdNBR was a good predictor of CBI field measurements ($r^2 = 0.78$; Fig. 2). In contrast with other studies that have compared dNBR to CBI values (Van Wagtendonk et al., 2004; Alexander et al., 2006), the relationships between the CBI and RdNBR we obtained were linear. Of the 1.4 million ha Gila National Forest, 152,874 (about 11%) burned between 1984 and 2004, and 10% of the burned area was burned severely (Table 2) (note that this excludes those areas that burned more than once 1984–2004). The percentage of area burned with low, moderate and high severity varied among vegetation types (Table 2). The upper elevation spruce-fir and mixed-conifer forests PVTs had the highest proportion of the area burned severely (Table 2). Severely burned areas were found disproportionately in mesic PVT's, on north and northeast-facing slopes (azimuth 315–360 and 0–90°), on steep slopes (>16%), and where solar radiation values were low to moderate (99–113 kWH/m^2) (Fig. 3a–d). Severe fire occurrence was also associated with low CTI values, where heat load (HLI) was either very low or very high, at high elevations and high slope position values, likely reflecting the tendency for severe fire to occur at the crest of hills (Fig. 3e–h). These patterns are consistent with those observed in the field and those experienced by local fire managers.

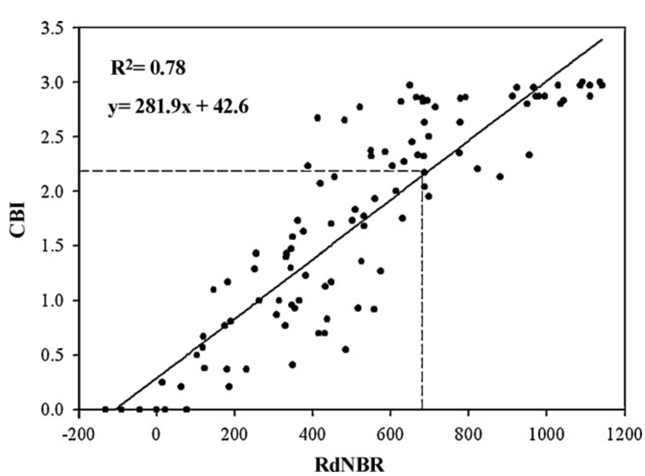

Fig. 2. Modified Composite Burn Index (CBI) from 109 field plots vs. the differenced Relative Normalized Burn Ratio (RdNBR) collected on the 2003 Dry Lakes Fire, New Mexico. Data were collected between 20 May 2004 and 20 July 2004, 1 year after the 2003 fire. Dashed lines show threshold between "moderate" and "severe" burn severity classes (CBI = 2.2; RdNBR = 665).

Classification accuracy of Random Forest models on all PVTs combined was 79.5% and 64% for two and three burn severity classes, respectively (Table 3). With the exception of the spruce-fir PVT, classification accuracy decreased slightly across a gradient from dry (Pinyon–Juniper) to wet (mixed-conifer) PVT's (Table 3).

4. Predictive model development

The Random Forest model described above was used to build a predictive model surface for the Gila National Forest using the Random Forest prediction function available in R (Fig. 4) (Liaw and Weiner, 2002). The final Random Forest model used to build the prediction surface was created from a random stratified sample of 23,000 pixels, stratified by two severity classes (severe vs. all other burn severity classes) and PVT. This dual-phase stratification approach ensured that the sample distribution was balanced across each severity class and that it represented a range of biophysical settings. Each predictor variable used in the Random Forest model was built, clipped to the extent of the Gila National Forest and then converted to ASCII text files with matching extents and projection. The Random Forest algorithm implemented in R contains a prediction function that assigns each output cell to a class based on the majority vote counts of the terminal nodes from each classification tree in the model. We modified this output by programming a function to convert the vote counts to probability distributions, rather than a straight class prediction. Thus, each 30 m cell in the prediction surface was assigned a probability of burning as "high severity" based on its underlying topographic characteristics. This gives much more flexibility in interpretation and use of the final predictive model surface.

5. Discussion

The relationship between burn severity and topography reflects the influence of biophysical gradients on site productivity and vegetation. Forest ecosystem productivity in the southwestern US is primarily water-limited (Chapin et al., 2002), and topographic factors like elevation, slope aspect and Compound Topographic Index (CTI) influence biomass production and fuel accumulation

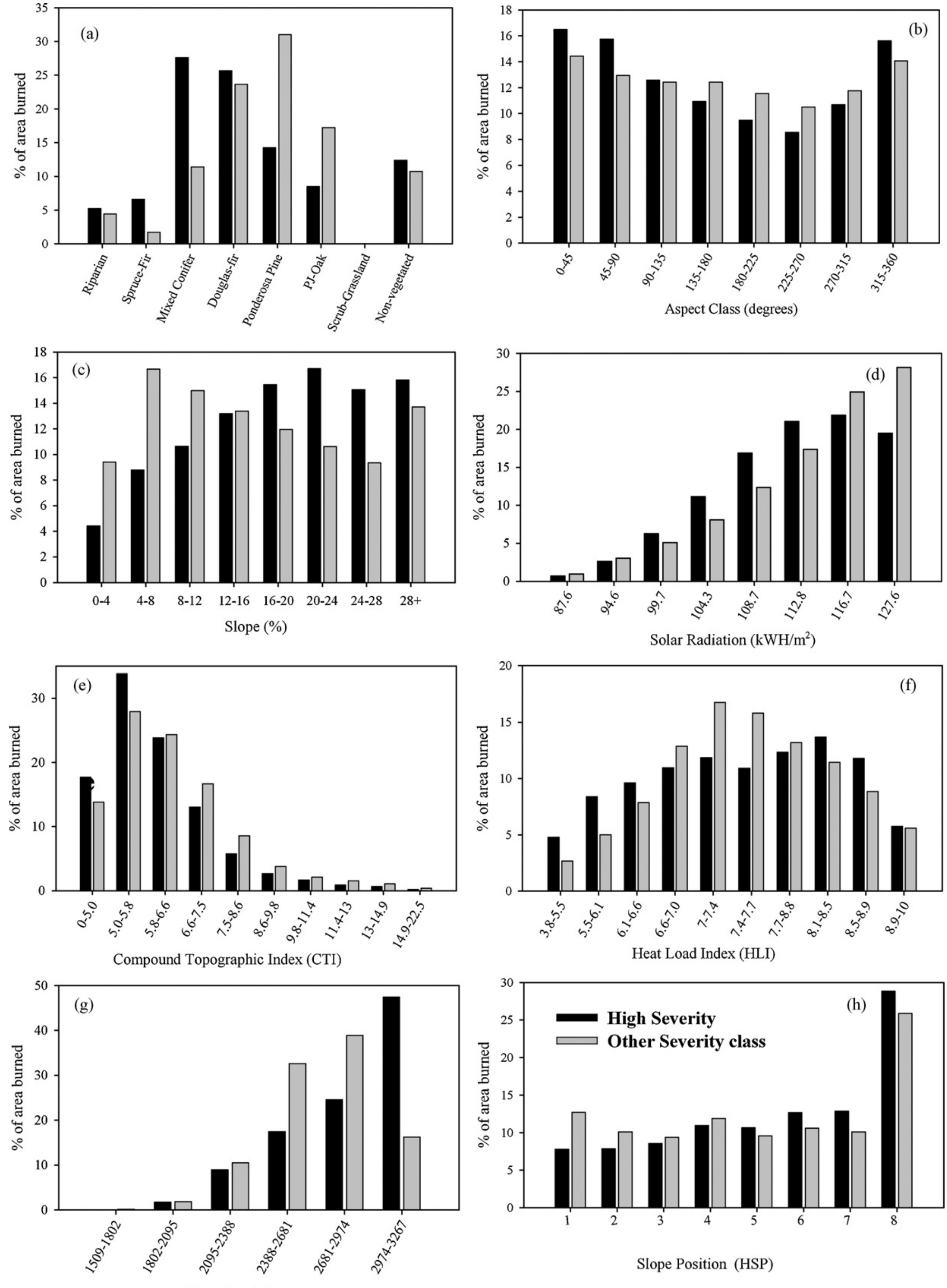

Fig. 3. Bayesian conditional probability of severe fire occurrence for (a) Potential Vegetation Type, (b) aspect class, (c) slope class, (d) cumulative April–June solar radiation class, (e) Compound Topographic Index class, (f) Heat Load Index class, (g) Elevation class and (h) slope position class. Black bars indicate percentage of total area burned that was classified as burned severely. Grey bars show percentage of area in all other burn severity classes. Black bars higher than grey bars for an individual class indicate a higher proportion of severe fire occurring in that class relative to the total area that was burned.

Table 3
Classification error rates and important predictor variables from Random Forest models for all PVTs and each PVT analyzed separately using a 2-class (high vs. other burn severity) and 3-class (low, moderate, high severity) RdNBR grid.

PVT	Classification error Severity classification		Important variables
	2-Class	3-Class	
All PVTs	20.5%	38.3%	ELEV, SAT, ROUGH27, HSP
Spruce-fir	14.6%	25.0%	ELEV, ERR15, SAT, HLI
Mixed-conifer	24.6%	40.4%	ELEV ROUGH27, SAT, HSP
Douglas-fir	23.2%	40.7%	ELEV ROUGH27, SAT, HSP
Ponderosa pine	22.9%	39.3%	ELEV, ROUGH27, HSP, SAT
PJ-Oak	19.3%	37.3%	ELEV, HLI, SAT, HSP
Riparian	18.0%	29.2%	ELEV, CTI, HSP, SAT

See Table 1 for abbreviations.

rates. Even slight increases in effective moisture can lead to significant changes in vegetation structure, such as Douglas-fir encroachment on slightly north-facing slopes and ponderosa pine establishment at mesic sites within areas dominated by pinyon and juniper. This pattern appears to shift in upper elevation mixed-conifer and spruce-fir forest types, where increased solar insolation and Heat Load Index values, factors that would increase evapotranspiration and drying of surface fuels, are associated with increasing burn severity. This general pattern is supported by Random Forest model results. Classification accuracies are highest for dry vegetation types and decrease across a gradient from dry to moist sites. Classification accuracy then increases significantly within the highest elevation spruce-fir forests.

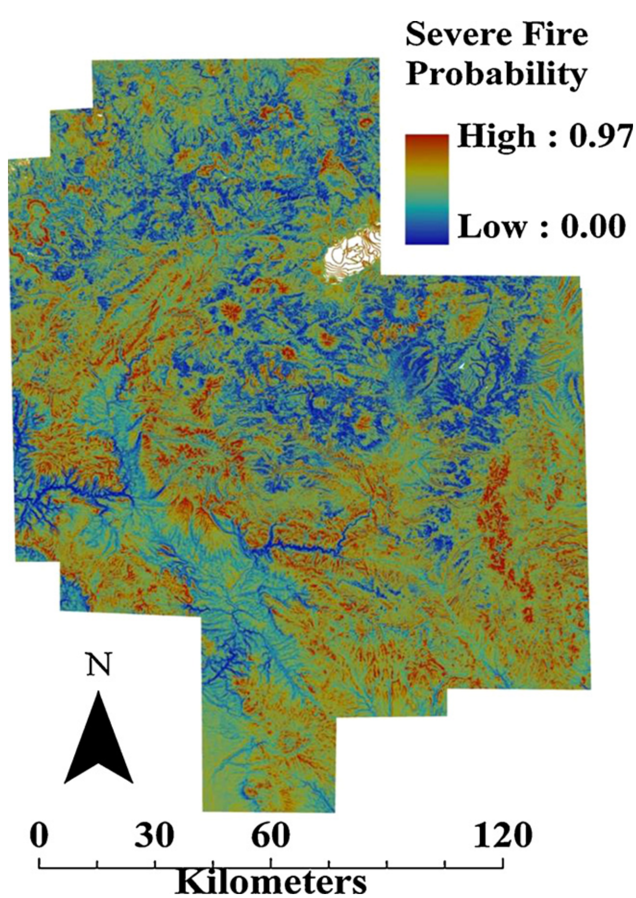

Fig. 4. Random Forest model prediction surface for the Gila National Forest. Each 30 m^2 cell is assigned a probability of that cell burned severely based on its underlying topographic characteristics. Note that low elevation grass and shrub-dominated areas to the North and East have been excluded from the predictive model.

Winter precipitation combined with the timing and intensity of precipitation events during the fire season influences green-up patterns in our study area, with the length of the dry period preceding summer monsoon rains influencing fire occurrence, presumably by affecting vegetation productivity and stress. Combined with temperature, relative humidity and the timing and intensity of monsoon rains, these precipitation variables should largely determine fuel moistures and the length of the burning window during the fire season, which in turn influences fire extent and severity (Holden et al., 2007). The length of this window is shorter at higher elevations, where snow pack delays early season green-up. Within the drier PVTs at lower elevations, spring precipitation patterns influence the peak and subsequent decline of green-up preceding monsoon rainstorms. We speculate that these patterns are reflected in the patterns of severe fire occurrence in this landscape (Holden and Morgan, in review). At lower elevations, dry PVTs have a long window within which burning is possible. At locally wet and more productive sites, higher vegetation density and fuel accumulation means that the effects of fire will be more severe (greater change pre- to post-fire). Given the relatively short burn window within high elevation, mesic vegetation types, extremely cool, wet areas (e.g. those at high elevation, north-facing slopes) may not have experienced ignition when conditions were favorable for burning during this study period. In contrast, fuels on dry and relatively warm south-facing slopes within these cool sites will dry earlier and thus be available for burning should ignition occur.

The strength of relationships between severe fire occurrence and topographic variables may also reflect connections between topography and fire behavior. Slope aspect position influences the type of vegetation that will occur on a site as well as drying rates of live and dead fuel moistures, directly influencing fire intensity when fire occurs. Slope steepness is known to directly influence fire rate of spread (Rothermel, 1972). Other topographic features like slope curvature and topographic complexity (described by variables like the Elevation Relief Ratio (ERR) and topographic Roughness (ROUGH)) may exert more subtle influences on fire behavior by influencing microclimate, wind patterns or the length of wind-driven fire runs. They also reflect soil development and water holding capacity.

Taken together, these results support the idea that climatic and topographic controls on fire regimes are hierarchical (Heyerdahl et al., 2001). The strong relationship between topography and burn severity reflects the "bottom up" topographic and vegetation control of burn severity occurrence and the tight coupling of climate, topography and vegetation in this semi-arid region, where moisture limits vegetation production. The limited human influence on the fuels and vegetation in the majority of fires that burned within the wilderness has allowed these fire–vegetation–topography interactions to play out for decades. Random Forest predictions decrease in their classification accuracy from dry to moist vegetation types (Table 3), which suggests that vegetation–topographic coupling and its influence on fire behavior breaks down in wetter vegetation types. We hypothesize that the relative amount of change in vegetation accumulation within drier vegetation types in the absence of recent fires would have been greater in dry forests than in upper elevation PVTs, where historically, fires were less frequent (Abolt, 1996).

6. Study and model limitations

There are several important limitations to the analyses presented here. First, we have by necessity used relationships between field measures of burn severity in a single large fire in

2003 to assign severity classes to all fires. Timing of image acquisition and vegetation phenology at the time of image acquisition will all influence the pre- and post-fire image reflectance and hence the RdNBR spectral index values for each fire. Lacking field data for these earlier fires, it is impossible to validate the burn severity classifications assigned to these fires. To account for this potential error, we used carefully matched pre- and post-fire images that were within 20 days of each other. Second, we used what we consider a conservative threshold (>75% overstory canopy brown or red) to assign the break between severe and all other classes. Our experience in the field and with several years of working with these data has shown that the dNBR and RdNBR indices are quite good at capturing areas of complete overstory vegetation removal post-fire. Nonetheless, there is undoubtedly some error introduced in the assignment of fixed severity thresholds using thresholds derived from image and field data from a single image. Such errors would in turn affect the resulting model accuracy and prediction.

Temporal and spatial patterns of severe fire occurrence inferred from only twenty years of data should be interpreted cautiously. We have not accounted for the influence of vegetation structure, which influences burn severity, nor did we analyze climate and weather data. Although some of the fire years included in this study were very wet (e.g. 1984–1987) and others were very dry (e.g. 2002) we cannot assume that these data encompass the full range of possible fire–vegetation–climate interactions. We also note the potential significance of fire origin and direction of travel in this study area. For example, because most fires during the last 20 years have started in central portions of the Gila Wilderness and spread to the north, many north-facing slopes experienced backing fires. We observed in the field many north-facing slopes at mid-elevations dominated by ponderosa pine and Douglas-fir forest types that had experienced surface fires at least once during the last 20 years, despite relatively dense stands and young understory Douglas-fir tree encroachment. When these north-facing slopes finally experienced a fire that began outside the wilderness and spread to the south, many of them burned as stand-replacing fires. We cannot rule out the possibility that wind direction and other aspects of weather and fuels not evaluated here may also be responsible for the severity patterns observed within mixed-conifer and spruce-fir forest types.

7. Implications for management

One impetus for this analysis was concern from land managers about the impacts of fires in the Gila Wilderness on endangered Gila trout populations (*Oncorhynchus gilae*). Debris flows following fires in 1995, 2002 and 2003 severely impacted or extirpated several local populations of these fish (Probst and Monzingo, land managers, Gila National Forest, personal communication). Knowing what areas are most likely to burn severely can help local land managers in their decisions about fire management before, during and after fires within areas inhabited by Gila trout.

Interpreting burn severity from satellite data for hundreds of fires across a range of environments and climatic conditions will greatly enhance our understanding of why and where fires burn severely. Such analyses will help us to strategically target fuels and fire management. They may also help us better understand the climate and weather conditions under which fire management options like Wildland Fire Use may or may not be appropriate.

Our predictive model should be used with caution, as the post-fire ecological effects of any particular future fire will likely vary with the local weather and fuels conditions. The model's predictive capability of landscape and topographic variables alone, without data on pre-fire surface fuel loading and forest structure, and without during-fire weather, was greater than 79% overall, and slightly higher within individual PVTs. Data on these variables as well as on past fires and vegetation conditions could help improve our ability to predict where and when fires are likely to burn severely.

Logging, grazing, and other vegetation disturbances will likely alter the vegetation–topography relationships, confounding the prediction of burn severity in future fires. Further evaluation of burn severity–topography interactions across a range of environments, vegetation types and land uses will be necessary to understand how these patterns vary across space.

Understanding the complex interactions among fire, vegetation, topography, climate, land use and disturbance is critical to predicting how fire regimes will change in response to climate and future land use (Morgan et al., 2001). Our current understanding of burn severity as an aspect of fire regimes is mainly theoretical or based on anecdotal evidence and case studies from a few fires. We hope this effort and the one by Miller et al. (2009) will be the first of further efforts to evaluate patterns of burn severity across multiple fires over multiple years. Through the Monitoring Trends in Burn Severity (MTBS) project, data similar to ours are now available nationwide for thousands of fires. These data will be immensely valuable for understanding burn severity to complement our growing understanding of fire extent and fire occurrence relative to climate, land use, vegetation, topography and disturbance. In future analyses, we will extend the predictive modeling described here to forested areas of the western US.

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